African Journal of Business Management Vol. 6(2), pp. 690-703, 18 January, 2012
Available online at http://www.academicjournals.org/AJBM
DOI: 10.5897/AJBM11.2492
ISSN 1993-8233 ©2012 Academic Journals

Full Length Research Paper

Personality for buyer and seller agents in electronic marketplace based on reputation and reinforcement learning

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Accepted 7 October, 2011

In this paper, we propose a marketplace model which is based on personality, reputation and reinforcement learning algorithms for buying and selling agents. We use two personality traits for seller agents: stingy and conscientiousness. In this marketplace, sellers with low score of stingy earn more benefits in comparison with high stingy sellers. Also, conscientious seller agents gain more reputation relative to conscienceless seller agents. In addition, we use three personality traits for buyer agents: stingy, openness and agreeableness. Buyer agents with high score of openness and low score of stingy purchase more new goods and more expensive goods relative to buyers with low score of openness and high score of stingy. Buyer agent's seller with high score of agreeableness would be less cheated in the marketplace. Also, buyer agents apply reinforcement learning to evaluate the reputation of seller agents and then focus their trading on reputable sellers. On the other hand, the personality of seller agents affects them to consider discount for buyer agents. In addition, seller agents apply reinforcement learning to establish a model of reputation of buyer agents. The results show that selling/buying agents that model the reputation of buying/selling agents obtain more satisfaction rather than selling/buying agents who only use the reinforcement learning.

Key words: Agent, marketplace, personality, reputation, reinforcement learning.

INTRODUCTION

The growing prevalence of internet access has enabled new markets to emerge online. Internet has also allowed less common marketplaces to thrive by connecting buyers and sellers from disparate locations. The formation of online marketplaces often occurs quickly in response to social or economic trends.

Mobile agent-based architectures have been proposed for the business models, particularly in e-marketplaces, each participant can be associated with specific goal-driven mobile agents; the management agents can support e-marketplace authorities, personalized selling agents can play the role of suppliers, and buying agents can represent end-consumers. Every day, millions of people engage in commercial transactions over the internet, using portals such as Amazon and eBay. The revolutionary feature of these electronic marketplaces is that they enable traders to transcend the limits of geographic distance by providing them with a platform to exchange goods and services without ever meeting their interaction partners (Ba and Pavlou, 2002). However, there is a trade-off. The increased opportunity for trade comes with a significant increase in the risk involved. Buyers and sellers in an electronic market are likely to be complete strangers and are separated by physical distance. This leads to an information asymmetry between them. The seller often has a much better idea about the true value of the product than the buyer does. The buyer pays first and has no way to enforce that the seller fulfills the transaction as agreed. The seller can act in a number of ways that are detrimental to the buyer's welfare. The most extreme scenario is one where the seller receives payment and does not ship the product at all. There are several other possibilities such as intentional misrepresentation of product quality, or use of inferior shipping material, that can lead to an unsatisfactory transaction for the buyer.

Many electronic marketplaces employ a reputation system to solve the moral hazard problem and induce trustworthy behavior from the seller. A reputation system removes the disconnection between the present and the future, by making a record of the seller's past transaction outcomes available to potential buyers. A reputation system collects information about the participants' past behavior, aggregates this information, and makes it available to other participants. We have seen earlier that electronic markets do not achieve folk theorem like efficiency due to the lack of repeated interactions and persistent identities. A reputation system attempts to redress both these issues. Even though a user can be identified only by a pseudonym, the reputation system reveals the history of his interactions with other users. Now, even if a buyer does not know the identity of the seller she is dealing with, she knows how he has behaved in his past transactions. Similarly, the seller knows that even if he does not encounter this particular buyer again, potential buyers in the future can base their purchase decisions on the outcome of this transaction (Fischbacher, 2007). A reputation system performs the following functions (Resnick et al., 2006):

i. Signaling: A reputation system enables the buyer to distinguish between trustworthy and untrustworthy sellers. A seller's reputation acts as a signal of his skill and integrity. Buyers can use this information to distinguish dishonest and incompetent sellers from good ones, thereby overcoming adverse selection.
ii. Sanctioning: A reputation system reveals the seller's past actions to future buyers. Sellers, aware that their actions are being reported and that future buyers can discriminate against sellers with a bad reputation, have an incentive to act in a trustworthy manner. The reputation system thus helps the sellers overcome moral hazard.
iii. Self-selection: Another consequence of the reputation system is that sellers, who are incompetent or dishonest, acquire a bad reputation and are not able to attract buyers. Eventually, such sellers will be driven out of the market. Thus, the reputation system helps limit adverse selection.

The main goal of agents' research is building human-like agents. In this situation, applying personality traits to electronic commerce agents make them more realistic and human-like.

In this paper, we propose a model based on personality for buyer and seller agents in agent-based electronic marketplaces. We consider two personality traits for seller agents: stingy and conscientiousness. Stingy is a negative facet of agreeableness trait (Kevin and John, 2006). Stingy seller agents are the sellers who like money so much, and try to maximize their benefits. Therefore, these seller agents consider a little discount for buyers. In other words, high score of stingy implies considering low discount and vise versa. Also, seller agents with personality trait conscientiousness are responsible, dutifulness and orderly. These sellers try to be trustful in the market. Their bids are compatible with the characteristics of their real goods. They do not lie about their goods and not try to cheat the buyers. High score of conscientiousness means, high dutifulness and conscientious and vise versa.

In addition, we use three personality traits for buyer agents: stingy, openness and agreeableness. Price of the goods is very important for stingy buyers. They focus on low price goods. Low score of stingy means that buyer agent is more spendthrift and prodigal. The price of goods is not so much important for the buyers with high score of spendthrift (low score of stingy). The other trait which is considered for buyer agents is openness. Researches show that openness trait is positively related to hedonic product value (Matzler, 2006). Buyer agents with these characteristics tend to purchase new and hedonic products. This tendency depends on their openness score. Next trait that we use for buyer agents is agreeableness. People who score high on this dimension are empathetic, considerate, friendly, generous, and helpful. They also have an optimistic view of human nature. They tend to believe that most people are honest, decent, and trustworthy. People scoring low on agreeableness place self-interest above getting along with others. High score of agreeableness means that buyer agents trust to other buyers and use other buyers' knowledge to know honest and dishonest sellers in marketplace.

LITERATURE REVIEW

Buyer and seller behavior research involves various areas: psychology, marketing, sociology, economics and engineering (Zhang and Zhang, 2007). Some researches on reinforcement learning and reputation, in addition to the relation between consumer behavior and personality will be discussed later in this paper.

Reinforcement learning and reputation

The reinforcement learning problem is the problem of learning from interaction to achieve a goal. In this problem, an agent observes a current state (*s*) of the environment, performs an action (*a*) on the environment, and receives a feedback (*r*) from the environment. This feedback is also called reward, or reinforcement. The goal of the agent is to maximize the cumulative reward it receives in the long run.

Reinforcement learning has been applied extensively in various learning problems for agent and multi-agent systems. This is reflected by the growing number of publications in the area (Matzler, 2006; Littman, 1994; Nagayuki et al., 2000; Nagendra et al., 1996; Ono and Fukumoto, 1996; Sandholm and Crites, 1996; Tan, 1993;

Sen et al., 1994; Weiss, 1993, 1997). Sen et al. (1994) addresses the problem of how multiple agents can learn to appropriately coordinate their activities in order to accomplish a common task. In particular, they apply the Q-learning algorithm to a block pushing problem, the problem in which multiple agents are independently instructed to move a block from a starting position to some goal position. Their work shows that agents can learn complementary strategies to fulfill a common task without any knowledge about each other. The main result presented in Sen et al. (1994) is that although individual agents are independently optimizing their own environmental rewards, global coordination between the agents can be obtained without any explicit or implicit form of communication.

Weiss (1993) addresses the problem of coordination in multi-agent systems using a different approach. According to his approach, agents learn to coordinate their actions by explicitly communicating with one another. He introduces two reinforcement learning based algorithms called the Action Estimation (ACE) algorithm and the Action Group Estimation (AGE) algorithm. In both algorithms, the agents first learn to estimate the goal relevance of their actions. They then coordinate their actions and generate appropriate action sequences based on their goal relevance estimates. The main difference between the ACE algorithm and the AGE algorithm is that the agents executing the AGE algorithm do not compete for carrying out individual actions (as those executing the ACE algorithm), but for carrying out groups of actions.

In developing learning algorithms for agents in electronic marketplaces, we use a reputation mechanism, in addition to reinforcement learning, to provide added robustness to buying agents. By dynamically maintaining sets of reputable and disreputable selling agents, buying agents should together isolate and weed out dishonest selling agents, and therefore obtain better satisfaction in doing business with the reputable ones.

Tran and Cohen (Tran, 2005; Tran and Cohen, 2004, 2005) exploit reinforcement learning for buying agents to model the reputation of selling agents to protect buyers from communicating with non-reputable sellers. Nevertheless, buyers in this model should have fixed priorities on quality and price of their desired goods. In this way, they cannot change their preferences to buy a good in a sequence of purchases; that is, a buying agent can not purchase a good in an auction with priority on quality and willing to buy the same good in another auction with priority on price. In addition, selling agents do not model the reputation of buyers to consider discount and just only focuses on two factors of quality and price.

Personality and consumer behavior

There are two main models for personality: OCEAN (Wiggins, 1996) and Cattle (Conn and Rieke, 1994). OCEAN or Big Five model includes five factors: openness, conscientiousness, extraversion, agreeableness and neuroticism. Openness means a person is imaginative, independent-minded and divergent thinking. Conscientiousness describes the person who controls the impulse, following rules and norms. Also, they are responsible, dependable and orderly. Extraversion means that a person is talkative, social and assertive. Agreeableness means a person is good natured, co-operative, and trusting. Agreeableness is considered to be a superordinate trait, meaning that it is a grouping of more specific personality traits that cluster together statistically. There are exceptions, but in general, people who are concerned about others also tend to cooperate with them, help them out, and trust them. Neuroticism means a person is anxious, prone to depression and worries a lot (Taihua et al., 2007).

The other model is Cattle. This model categorize the personality into 16 traits: warmth, reasoning, emotional stability, dominance, liveliness, rule-consciousness, social boldness, sensitivity, vigilance, abstractedness, privateness, apprehension, openness to change, self-reliance, perfectionism and tension (Conn and Rieke, 1994).

There are some researches which prove that personality is strongly connected to consumer purchase decision making process. Copas (2004) focus on two personality traits for evaluating buyers online shopping: openness to change and vigilance. Results showed that vigilance, or suspiciousness, was negatively associated with Internet purchasing behaviors that required commitment such as giving credit card or personal information. Vigilance was also negatively associated with internet usage attitudes demonstrating a relationship between trust and Internet comfort levels. These results support the hypothesis that vigilance as a personality factor can influence internet shopping behaviors. Also, Results showed that the openness to change personality trait was positively associated with internet behaviors and attitudes. This supports the hypothesis that openness to change as a personality factor can influence internet shopping behaviors.

Mowen (2000) proposes 3M model for consumer online shopping behavior based on OCEAN model which has four traits: elemental, compound, situational and surface trait. According to this hierarchical model, genetic predispositions and early learning experiences determine the individual's elemental traits (for example, the Big Five) that combine with a person's socialization process to shape compound traits (for example, needs for arousal and cognition). Situational traits are further formed through interactions of compound traits and situational influences (for example, health motivation). Finally, surface traits (for example, bargain-proneness) evolve from situational traits and represent specific dispositions in response to the context.

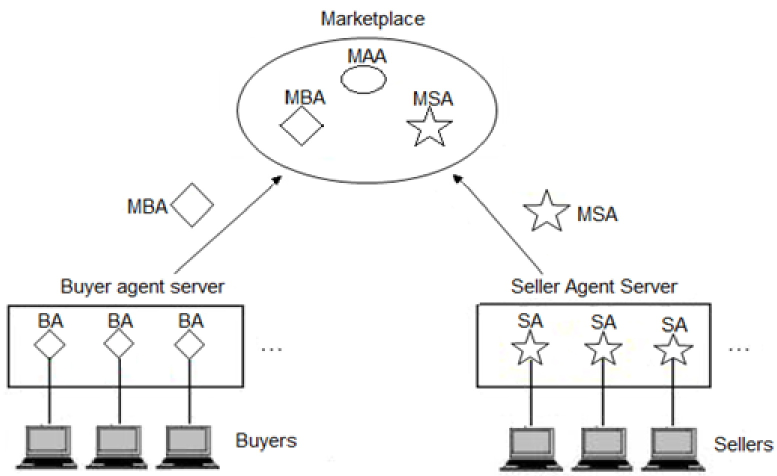

Figure 1. The framework of e-marketplace.

In addition, researches show that openness trait is positively related to hedonic product value and directly influence brand affect which in turn drives attitudinal and purchase loyalty (Matzler, 2006).

THE PROPOSED ALGORITHM

Our proposed reputation-oriented reinforcement learning algorithms for buyers and sellers in electronic market-places is presented here, respectively. The algorithms are aimed at maximizing the expected values of goods and avoiding the risk of purchasing low quality goods for buyers, and maximizing the expected profits for sellers. Note that it is possible for both a seller (s) and a buyer (b) to be winning in a business transaction. This happens when seller (s) could choose a price (p) to sell good (g) to buyer (b) that maximized its expected profit, and buyer (b) decided that purchasing good (g) at price (p) from seller (s) would maximize its expected value of goods. We also provide a simple numerical example to illustrate how the algorithm works. We propose a market model based on personality and reinforcement learning for buyer and seller agents. The transactions in market between buyer and seller agents are based on contract net protocol (Smith, 1980; Davis and Smith, 1983).

The key point of this work is considering the personality for buyer and seller agents. It is very important to mention that it is so complex to consider all personality traits for buyer and seller agents. Therefore, we have considered only three personality traits for buyer and two personality traits for seller agents which are more related to transactions in the market: Openness, agreeableness and stinginess for buyers and stingy and conscientiousness for sellers.

Framework of agent-based e-marketplace

The proposed framework of e-marketplace is shown in Figure 1. There are three types of server in the proposed architecture for e-marketplace, they are: (1) marketplace, (2) buying agent server, and (3) selling agent server. Each server includes several stationary agents and mobile agents and some important transactions between different agents in the marketplace. They are as described thus.

Marketplace

Marketplace is a platform that supports the transaction facilities for mobile agent of sellers and buyers. There is a static agent (MAA: market assistant agent) and two kinds of mobile agent in the marketplace:

1. MAA (market assistant agent): The MAA is responsible for registering mobile buying and selling agents in the buyer and seller database of marketplace. The buyer database of marketplace contains: owner of mobile buying agent, buying agent server, a unique identifier, and proxy address of agent provided by aglet context and time of registration. The seller database of marketplace contains: owner of mobile selling agent, selling agent server, a unique identifier, address proxy of selling agent provided by aglet context, goods which are available for mobile selling agent to sell and time of registration. Agent A can communicate with agent B through the proxy address of agent B and vice versa. Also, the MAA answers to the mobile buying agent request by retrieving proxy address of sellers, from seller database, who have good g to sell and send the list to the mobile buying agent.
2. MBA (mobile buying agent): stands for the buyer, moves to the Marketplace and trades with mobile selling agents and learns, based on reinforcement learning, that which sellers can satisfy its preferences. Also, the MBA measures the reputation of each mobile selling agent on different factors: quality, price and delivery and focuses its business on reputable sellers and prevent to interact with non reputable ones.
3. MSA (mobile selling agent): stands for the seller, moves to the Marketplace and trades with mobile buying agents and learns how to adjust its bids according to the preferences of the buying agents while trying to maximize its expected profit. Also, it models the reputation of mobile buying agents to dedicate discount for them based on their reputation.

Selling agent server

Each seller, who wants to join this e-marketplace, should build a seller server. There are two main Agents in a seller server, which include: (1) selling agent (SA): which is provided by selling agent server that lets the seller to initialize its selling agent and specify the

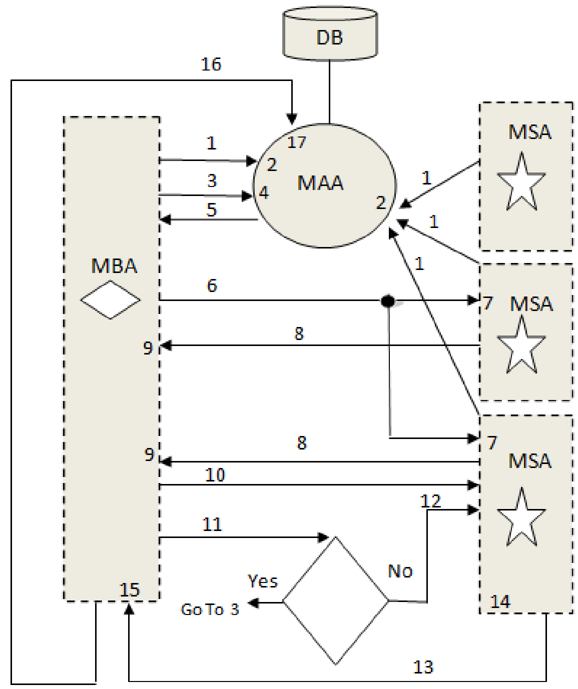

Figure 2. Transactions in agent-based e-marketplace (MAA: market assistant agent; MBA: mobile buyer agent; MSA: mobile seller agent; DB: database of mobile seller and mobile buyer agents).

goods which is available to sell, and (2) mobile selling agent (MSA): which is created by selling agent server and migrates to the marketplace and try to sell goods with maximum profit for its owner.

Buyer agent server

The buyer agent sever provides the web interface that lets users control their agents to carry the E-commerce activation out via standard Web-browser. Buying agent server stores the information of buyer in the database. There is a buyer server management agent (BSMA) that manages the buyer agent server. The BSMA will produce buyer agent (BA) for each user to serve its homologous user. BA will generate mobile buyer agent (MBA) according to the requirements of the user. The MBA stands for its user to go to every marketplace to make bargains.

Transaction in e-marketplace

In considering market which is a simulated environment by aglet, seller agents and buyer agents can present and perform needed transactions to accomplish their commercial affairs. This environment is on a computer, and buyer and seller agents are planed on it and purchase is done. A market assistant agent is carried into account that is responsible for registering seller and buyer agents information and assisting buyer agents to find seller agents proxy address that have considered product for selling. Seller and buyer agents after entering to marketplace do various transactions to buy or sell that are explained as follows (Figure 2):

1. BAs and SAs after run submit their personal information to MAA to register in marketplace.
2. MAA receives the information and stores in database. This database contains related fields to SA's and BA's information.
3. BA requests from MAA for list of specified goods (g) sellers to buy (through sending a message).
4. MAA retrieves relevant sellers for requested product.
5. MAA sends list of g sellers with other buyers' reputation rating on quality and number of bought goods (N) from these sellers to BA.
6. BA multicasts its requests to relevant sellers for specified product with its number.
7. SAs based on their personality and BA reputation and requested number of goods prepare bid for BA.
8. Each of those SAs send bid to BA**.**
9. BA receives all bids, evaluates their value based on its personality and trust to various sellers then selects the best bid.
10. BA announces the chosen bid owner as winner SA.
11. If BA requests another type of goods will go to stage 3.
12. BA pays the cost of goods to chosen SAs.
13. The winner SAs delivers the goods to BA.
14. SAs who could sell the products to BA, updates the BA's reputation based on their personality and obtained interest.
15. BA estimates the real value of products and updates the reputation of those SAs.
16. BA sends to MAA the number of bought goods with updated reputation on quality related to SAs.
17. MAA saves the sent information of BA in its database.

Thus, in our market environment, a buyer tries to find those sellers whose goods best meet its demanded value, while a seller tries to maximize its profit by setting suitable prices for and providing more customized value to its goods, in order to satisfy the buyers' needs. By considering some assumptions, we make the market more realistic and simpler. Therefore, we assume that:

1. Quality and price offered by different selling agents can be variable.
2. Each selling agent considers discounts for buying agents based on its personality and their reputation.

3. There may be some dishonest selling agents in the market who lie on quality and price.
4. Buying agents in the market are not dishonest.
5. A buyer can purchase a good in different conditions with variant priorities on quality and price instead of fixed priorities.
6. Each buyer has his own preferences and priorities on quality and price.
7. Product delivery is done by transferring message between seller and buying agents.
8. Maximum quality of a good presented in the market is definite so that all selling and buying agents know that.
9. Buyer can estimate the quality of the good he purchases only after receiving the good from the selected seller.

Seller algorithms

Let S be the set of sellers, G be the set of goods, B be the set of buyers, Q be the set of qualities and P be the set of prices, and S, G, B, Q and P are finite sets (It means that $q_{min} \in Q$ and $q_{max} \in Q$ represent minimum and maximum quality of goods that can be available in the market and all sellers and buyers know this). Assume that seller $s \in S$ has received a request from buyer $b \in B$ on good $g \in G$ with the N number of g. Seller s has to decide on the quality and price of good g to be delivered to buyer b. Assume that R be the set of real numbers. Let function e^s:G$\times Q \times P \times B \rightarrow R$, estimate the expected profit for seller s if it sells good g with quality q at price p to buyer b.

Assume that function $c^s(g,q,b)$ be the function for calculating the cost of good g, with quality q for buyer b. Seller s produce different versions of good g based on buyers requirements. The price that seller s chooses to sell good g to buyer b is greater than or even equal to $c^s(g,q,b)$. $stingy_s$ and $cons_s$ are the score of stingy and conscientiousness of seller s, respectively. These two values specify the personality of seller s. we show the personality of seller s based on these two personality traits as follows:

$$P^s = [stingy_s, cons_s] \quad stingy_s, cons_s \in [0,1] \qquad (1)$$

Assume that seller s produces good g with the cost of $c^s(g,q,b)$, the maximum price for seller s is evaluated as follows:

$$p_{\max} = c^s(g,q,b) + c^s(g,q,b) * (\kappa) \qquad (2)$$

In which, $k \in [0,1]$ is the reasonable score of profit based on market norms for seller s. After receiving the buyer request for good g, seller s adjusts the bid for the buyer. This bid includes two factors: quality and price. There are some sellers who try to cheat the buyers by offering high quality goods and delivering them low quality goods. In other word, these sellers do not say the real quality of their goods. For example, they have good g with quality q=50 to sell. However, they offer their good with quality more than 50, for example q=60, and then deliver the good with quality 50 to the buyer. In this situation, buyer b evaluates the good with quality 60 and may select it to purchase. Lying about the characteristics of the goods really depends on the score of conscientiousness of the seller and number of good g. Seller s adjusts the bid on quality by equation (3):

$$q_s = q_{real} + \left(\frac{q_{real} * (1 - cons_s)}{N}\right) \qquad (3)$$

In which, q_s is the quality which is offered to buyer, q_{real} is the real quality of the good, $cons_s$ is the score of conscientiousness of the seller and N is the number of goods that buyer b has requested. It is clear that high score of conscientious of seller and high N, cause q_s be closer to real quality and vise versa. Also seller s adjusts the bid on price by equation (4):

$$p_s = p - discount \qquad (4)$$

$$p = c^s(g,q,b) + ((p_{max} - c^s(g,q,b)) * stingy_s) \qquad (5)$$

$$discount = \left(p - c^s(g,q,b)\right) * r^s(b)(1 - stingy_s) \qquad (6)$$

Where, $r^s(b)$ is the reputation of buyer b from seller s that the default value of reputation is zero ($r^s(b) = 0$). When seller s sends his bid (q_s, p_s) to buyer b, there are the two following possibilities:

i. Assume that seller s succeeds to sell good g with quality q_s at price p_s to buyer b. It means that seller s has presented a bid better than the other sellers' bids to buyer b. Seller s delivers product to buyer b and updates the reputation of buyer b using reinforcement learning based on the equation as follows:

$$\sum_{i=1}^{N} (r^s(b) = r^s(b) + \mu_{profit} * (1 - r^s(b)) \qquad (7)$$

Where, μ_{profit} is a positive factor called cooperative factor that is equal to:

$$\mu_{profit} = \frac{profit}{profit_{max}} = \frac{p - c^s(g,q,b)}{p_{max} - c^s(g,q,b)} \qquad (8)$$

According to Equations 6 and 7, if the number of goods have been purchased by buyer b were more, in future auction buyer b get more discount from seller s.

ii. Now assume that seller s does not succeed to sell good g with quality q_s at price p_s to buyer b; in this situation, seller s has to reduce the price of the good to sell the good in another transaction to buyer b. It is clear that if seller s continues the previous bid, he cannot sell the good. He alters his bid based on equation (9):

$$p_{new} = p_s - (rp * p_s) - \left(\frac{1 - stingy_s}{10} * r^s(b) * p_s\right) \qquad (9)$$

Let rp be a variable that specifies the reduction percent of price for seller who want to deliver his product late. That is, he should reduce the price of his product according to this value. if $p_{new} < c^s(g,q,b)$, then seller s does not suggest the same good with previous quality. So that, he may optionally raise the value of quality by increasing its production cost as follows:

$$c^s(g,q,b) = (1 + inc)c^s(g,q,b) \qquad (10)$$

Where, inc is a specific constant called Sellers' quality increasing factor.

Buyer algorithms

Assume that buyer b wants to buy good g. Buyer b broadcasts his request to all sellers which they have good g to sell (according to what was discussed in proposed algorithm, list of these sellers has been already retrieved from MAA.). Sellers answer the request by sending bids to buyer b. Buyer b receives all bids and selects the suitable bid. Buyer b models the reputation of all sellers and selects the suitable bid from a reputable seller. Buyer b models the reputation of each seller based on two factors of quality and price, separately. To model the reputation of each seller, buyer b uses functions $r_q^b : S \longrightarrow (-1,1), r_p^b : S \longrightarrow (-1,1)$ that are called reputation function of b based on factors quality (q) and price (p), respectively. For example, $r_q^b(s)$ represents the reputation of seller s on quality computed by buyer b. Initially, buyer b sets the reputation ratings $r_q^b(s) = 0$ and $r_p^b(s) = 0$ for every sellers $\in S$.

Seller s is reputable for buyer b on quality iff $r_q^b(s) \geq \Theta_q^b$,where Θ_q^b is buyer b's reputable threshold on quality ($0<\Theta_q^b<1$). A seller s is considered as disreputable for buyer b on quality iff $r_q^b(s) \leq \theta_q^b$,where θ_q^b is buyer b's disreputable threshold on quality ($-1<\theta_q^b<0$). Similarly, we define buyer b's reputable and disreputable thresholds based on price by replacing q with p in the afore inequalities.

Let $S_{r\_q}^b$ be the set of sellers with good reputation on quality to buyer b; that is; $S_{r\_q}^b$ contains the sellers that have served b with expected quality of b in the past and are therefore reputable on quality by b. Hence, $S_{r_q}^b \subseteq S$and is initially empty, that is:

$$S_{r\_q}^b = \left\{ s \in S | r_{r\_q}^b(s) \geq \Theta_q^b \right\} \subseteq S \qquad (11)$$

Also, let $S_{r\_p}^b$ be the set of sellers with good reputation on price. $S_{r\_p}^b \subseteq S$ and is initially empty too, that is:

$$S_{r\_p}^b = \left\{ s \in S | r_{r\_p}^b(s) \geq \Theta_p^b \right\} \subseteq S \qquad (12)$$

Assume that $S_{nr\_q}^b$ be the set of sellers with bad reputation on quality to buyer b; that is, $S_{nr\_q}^b$ contains the sellers that have served b with not expected quality of b and are known as non reputable sellers on quality by b. $S_{nr\_p}^b \subseteq S$ and is initially empty, that is:

$$S_{nr\_q}^b = \left\{ s \in S | r_{nr\_q}^b(s) \leq \theta_q^b \right\} \subseteq S \qquad (13)$$

Also, let $S_{nr\_p}^b$ be the set of sellers with bad reputation on price. $S_{nr\_p}^b \subseteq S$ and is initially empty too, that is:

$$S_{nr\_p}^b = \left\{ s \in S | r_{nr\_p}^b(s) \leq \theta_p^b \right\} \subseteq S \qquad (14)$$

The main part of buyer algorithm is estimation function and reputation modeling.

Buyer b uses estimation function to evaluate the value of each bid. We have used three personality traits for buyers: openness, stinginess and agreeableness. Openness of buyers means that they are interested to buy high quality and hedonic goods (Matzler, 2006). In addition, it is clear that stingy buyers focus on low price goods. Agreeableness of buyers means that they have trust to other buyers and use the experiences of each buyer. We present the personality of buyer as follows:

$$P^b = [open_b, stingy_b, agreeable_b] \quad open_b, stingy_b, agreeable_b \in [0,1] \qquad (15)$$

In which, $open_b$ means the score of openness of buyer b. $stingy_b$ means the score of stingy of buyer b and $agreeable_b$ means the score of agreeable of buyer b, also $open_b + stingy_b = 1$. We define the buyer b's general reputable threshold based on it's personality as follows:

$$\Theta^b = open_b * \Theta_q^b + stingy_b * \Theta_p^b \qquad (16)$$

While buyer b's general disreputable threshold is:

$$\theta^b = open_b * \theta_q^b + stingy_b * \theta_p^b \qquad (17)$$

In the same way, we calculate the general reputation of seller s as follows:

$$r^b(s) = open_b * r_q^b(s) + stingy_b * r_p^b(s) \qquad (18)$$

Let S_r^b and S_{dr}^b be the sets of reputable and disreputable sellers to buyer b respectively, that is:

$$S_r^b = \left\{ s \in S | r^b(s) \geq \Theta^b \right\} \subseteq S \qquad (19)$$

And

$$S_{nr}^b = \left\{ s \in S | r^b(s) \leq \theta^b \right\} \subseteq S \qquad (20)$$

In which Θ^b and θ^b are general reputable threshold and general disreputable threshold, respectively. Buyer b will focus his business on the reputable sellers and stays away from disreputable ones.

The bid offered by seller is determined by $bid(q_s, p_s)$. Buyer b evaluates each of bid value among offered bids by various sellers based on its personality and sellers' reputation and then selects the best bid. The buyer b at first, based on Equations 21 and 22, guesses the quality q_s of offered by sellers regarded to its personality and reputation of each seller which we represent it with q_s^{guess}. To guess the quality q_s of each seller's bid, buyer b uses function $trust_q^b : S \longrightarrow [-1,1]$ that is called trust quality function of buyer b based on its personality. $trust_q^b(s)$ is the trust of seller s on quality computed by buyer b:

$$trust_q^b(s) = \left((1 - agreeable_b) * r_q^b(s) \right) + \left(agreeable_b * \frac{\sum_{i=1}^{m} (r_q^{b_i}(s) * n^{b_i})}{\sum_{i=1}^{m} n^{b_i}} \right) \qquad (21)$$

Where m is the number of other buyers that have bought goods from seller s, $r_q^{b_i}(s)$ is the reputation of seller s on quality computed by buyer b_i, n^{b_i} is the number of total goods that have been bought from seller s by buyer b_i. So, the q_s^{guess} of q_s based on its trust quality function is calculated by buyer b as follows:

$$q_s^{guess} = \frac{q_s + (trust_q^b(s)) * q_s}{2} \quad (22)$$

In Equations 21 and 22, if the agreeableness score of buyer b be high, in guessing the quality of q_s, the reputation of other buyers to seller is more valued. If the agreeableness of buyer b be low, buyer would consider more value for its reputation related to seller.

Buyer b guesses the value of bids offered by each seller by using Equation 23. The bid offered by seller is determined by $G^b(q_s^{guess}, p_s, s)$:

$$G^b\left(q_s^{guess}, p_s, s\right) = open_b * \frac{q_s^{guess}}{q_{max}} - stingy_b * \frac{p_s}{p_{max}} \quad (23)$$

Where q_{max} is the maximum quality of good g in the market, p_{max} is the maximum price for good with quality q_{max} . Then buyer b selects the seller s_{win} who belongs to the set of reputable sellers for buyer b whose bid value for buyer b is more than the other sellers' bid, that is:

$$s_{win} = \arg\ \max G^b(q_s^{guess}, p_s, s) \quad (24)$$

$$s \in S_r^b$$

Where, arg is an operator such that arg $G^b(s)$ returns s. In addition, if no sellers in S_r^b submit bids for delivering g (i.e.,$S_r^b = \emptyset$), then buyer b has to choose a seller s_{win} among sellers who are not reputable nor disreputable:

$$s_{win} = \arg\max G^b(q_s^{guess}, p_s, s) \quad (25)$$

$$s \in (S_r^b \cup S_{dr}^b)$$

Buyer b announces the seller s_{win} as winner seller. If buyer b requests, another type of good will go to stage 3 of proposed algorithm which is offered in transaction in e-marketplace discussed earlier, because it is possible that this seller wins in next stage again and sends all kinds of goods together, consequently the cost and time of sending goods will be reduced. If buyer b does not request another type of good and pays the cost of goods to chosen sellers then, the winner sellers deliver the goods to buyer b. After receiving the goods g from each s_{win} seller, buyer b examines the real quality of the goods. Assume that buyer b find quality $\hat{q}$ for each good has been delivered by s_{win} sellers. Then, buyer b evaluates and updates the reputation of each s_{win} seller based on each good.

Updating reputation on quality

There are two possibilities about the quality of good g:

i. If $\hat{q} \geq q_s$ then the reputation of s_{win} seller on quality is updated using reinforcement learning as follows:

$$r_q^b(s) = \begin{cases} r_q^b(s) + \mu_q(1 - r_q^b(s)) & if \quad r_q^b(s) \geq 0 \\ r_q^b(s) + \mu_q(1 + r_q^b(s)) & if \quad r_q^b(s) < 0 \end{cases} \quad (26)$$

Where, $r_q^s(s)$ means the reputation of seller s evaluated by buyer b. the default value of reputation of all sellers is equal to zero. $\hat{q}$ is the real quality which is examined by buyer b and q_s is the quality which seller s had offered. μ_q is a positive factor called the cooperation factor. μ_q is calculated as follows:

$$\mu_q = \begin{cases} (1 + open_b) * \frac{\hat{q} - q_s}{q_{\max}} & if \quad \frac{\hat{q} - q_s}{q_{\max}} > \mu_{\min\_q} \\ \mu_{\min\_q} & otherwise \end{cases} \quad (27)$$

That is, seller s_{win} offers good g with a quality greater than or equal to the value that buyer b demanded for quality of good g and therefore the reputation of seller s_{win} on quality is increased by Equation 27 accordingly. Also, (1+$open_b$) has been considered to show that buyers who are more of openness consider more reputation for sellers and vice versa. $\mu_{\min\_q}$ is a positive factor called minimum cooperation factor for quality.

ii. If $\hat{q} < q_b$ then the reputation of seller s_{win} on quality is updated as follows:

$$r_q^b(s) = \begin{cases} r_q^b(s) + \nu_q(1 - r_q^b(s)) & if \quad r_q^b(s) \geq 0 \\ r_q^b(s) + \nu_q(1 + r_q^b(s)) & if \quad r_q^b(s) < 0 \end{cases} \quad (28)$$

Where, ν_q is a negative factor called the non-cooperation factor. ν_q is calculated as follows:

$$\nu_q = (1 + \overline{open_b}) * \frac{\hat{q} - q_s}{q_{max}} \quad (29)$$

In which, $\overline{open_b} = 1 - open_b$ and $(1 + \overline{open_b})$ is called the penalty factor. The value of ν_q depends on the openness trait of buyer b. The greater value of openness trait causes the smaller value of ν_q and vice versa. It means that buyers who are more of openness, are more flexible in market and do not reduce the reputation of sellers, as much as low openness buyers.

Updating reputation on price

Let p_b be the expected price for the buyer b. There are two possibilities about the price of good g:

i. If $p_b \geq p_s$ then the reputation of seller s_{win} on price is updated using reinforcement learning as follows:

$$r_p^b(s) = \begin{cases} r_p^b(s) + \mu_p(1 - r_p^b(s) & if \quad r_p^b(s) \geq 0) \\ r_p^b(s) + \mu_p(1 + r_p^b(s) & if \quad r_p^b(s) < 0) \end{cases} \quad (30)$$

Where, μ_p is a positive factor called the cooperation factor. μ_p is calculated as follows:

$$\mu_p = \begin{Bmatrix} \overline{stingy_b} * \frac{p_b - p_s}{p_{max}} & if \ \frac{p_b - p_s}{p_{max}} > \mu_{min\_p} \\ \mu_{min\_p} & otherwise \end{Bmatrix} \quad (31)$$

In which, $\overline{stingy_b} = 1 - stingy_b$.That is, seller s_{win} offers good g with a price lower than or equal to the value that buyer b demanded for price of good g and therefore the reputation of seller s_{win} on price is increased by Equation 30 accordingly. It implements this fact that buyer b expects to buy goods with low price, therefore sellers who offer goods with lower price than the other, set more reputation on price for themselves to buyer b and those sellers have positive reputation on price that their price is lower than expected price of buyer b. μ_{min_p} is a positive factor called minimum cooperation factor for price. Also $(\overline{stingy_b})$ has been considered to show that buyers who are less stingy consider more reputation for sellers and vice versa.

ii. If $p_b < p_s$ then the reputation of seller s_{win} on price is updated using reinforcement learning as follows:

$$r_p^b(s) = \begin{Bmatrix} r_p^b(s) + v_p(1 - r_p^b(s) & if \ r_p^b(s) \geq 0 \\ r_p^b(s) + v_p(1 + r_p^b(s) & if \ r_p^b(s) < 0 \end{Bmatrix} \quad (32)$$

Where, v_p is a negative factor called the non-cooperation factor. v_p is calculated as follows:

$$v_p = (1 + stingy_b) * \frac{p_b - p_s}{p_{max}} \quad (33)$$

In which, $(1 + stingy_b)$ is called the penalty factor.

An example

For the purpose of illustrating how the proposed algorithm works, we provide a simplified numerical example including simple buying and selling situations, respectively.

Buying situation

Consider a simple buying situation where a buyer b announces its need of some good g to all sellers which they have good g to sell (according to what was discussed earlier in proposed algorithm, a list of these sellers with other buyers' reputation rating on quality and number of bought goods from these sellers has been already retrieved from MAA). Suppose that there are 5 sellers in the marketplace, namely $S = \{s_i | i = 1 \ldots 5\}$

Furthermore, suppose a seller can produce goods at the maximum quality of 50 and maximum price is 60. In addition, some parameters are applied for buyers as follows:

$\Theta_q^b = 0.52, \Theta_p^b = 0.34, \theta_q^b = -0.8, \theta_p^b = -0.5, open_b = 0.65, sting_b = 0.35$ and $agreeable_b = 0.6.$

Expected values for buyer b on quality and price are 40 and 45, respectively. We define μ_{min_q} in Equation 27 equals to 0.05, we also suppose $\mu_{min\_p} = 0.05$ in Equation 31 and buyer b needs 2 goods g (N=2). Assume that after some interactions between buyer b and sellers, the reputation rating on quality ($r_q^b(s_i)$) and the reputation ratings on price ($r_p^b(s_i)$) for each seller by buyer b are as in Table 1.

General reputation threshold and general reputation of sellers are computed based on Equations 16 and 18 respectively. General reputation of each seller is shown in Table 2:

$$\Theta^b = 0.65 * 0.52 + 0.35 * 0.34 = 0.457$$

So, sellers with general reputation equal or greater than $\Theta^b = 0.457, (r^b(s_i) \geq 0.457)$ are reputable to buyer b, hence seller s_1, s_2 and s_4 have the chance to be chosen by buyer b in current auction.

Also, set of reputable sellers updated by buyer b is based on Equation 19 as follows:

$$S = \{s_1, s_2, s_4\} \subseteq S$$

Assume that other buyers' reputation rating on quality and number of bought goods from these sellers have been sent to buyer b from MAA as shown in Table 3. After b's announcement of its request for good g to all sellers in which they have at least 2 goods g to sell, the sellers bid with the following specification to deliver g to buyer b have been shown in Table 4.

Buyer b calculates the trust of each seller s on quality according to Equation 21 and guesses the quality of each bid based on Equation 22 as shown in Table 5. Now, buyer b guesses the value of each bid offered by sellers based on Equation 23. Results are shown in Table 6. Then, buyer b selects the seller s_{win} who belongs to the set of reputable sellers for buyer b ($\{s_1, s_2, s_4\}$) whose bid value for buyer b is more than the other sellers by Equation 24. So, buyer b buys goods g from s_1 with guessed value $G^b(q_{s_1}^{guess}, p_{s_1}, s_1) = 0.2841$. The guessed value for good offered by s_5 is 0.293, but because this seller has not served b well in the past auctions and has been known as non reputable seller by b, therefore buyer b does not interact with seller s_5 and selects s_1 as winner of this auction and buys good g from s_1.

Suppose that after paying, seller s_1 deliver 2 goods g to buyer b then buyer b examines the quality of each good g and finds $\widehat{q_1}$= 50 for g_1 and $\widehat{q_2} = 44$ for g_2. Because buyer b bought 2 goods from seller s_1, Buyer b now updates the reputation of seller $s_1$on quality and price twice as follows:

i. First time for good g_1: Because $\widehat{q_1} \geq q_{s_1}$ (50$\geq$ 47), buyer b uses Equation 26 and 27 to update reputation on quality of s_1 . On the other hand, buyer b uses Equations 32 and 33 to update reputation on price because $p_b < p_{s_1} (45 < 48)$:

$$\mu_q = (1 + 0.65) * \frac{50 - 47}{50} = 0.099$$

$$r_q^b(s_1) = 0.8 + 0.099 * (1 - 0.8) = 0.8198$$

$$v_p = (1 + 0.35) * \frac{45 - 48}{60} = -0.0675$$

$$r_p^b(s_1) = 0.5 + (-0.0675) * (1 - 0.5)) = 0.4662$$

Table 1. Reputation ratings on quality and price of different sellers to buyer b.

s_i	s_1	s_2	s_3	s_4	s_5
$r_q^b(s_i)$	0.8	0.65	0.25	0.60	0.2
$r_p^b(s_i)$	0.5	0.25	0.5	0.2	0.35

Table 2. General reputation ratings of different sellers to buyer b.

s_i	s_1	s_2	s_3	s_4	s_5
$r^b(s_i)$	0.695	0. 51	0.3375	0.46	0.2525

Table 3. Other buyers' reputation rating on quality and number of bought goods of different sellers.

s_i	s_1	s_2	s_3	s_4	s_5
$(r_q^{b_1}(s), n^{b_1})$	(0.9, 15)	(0.6, 13)	(0.3, 2)	(0.32, 10)	(0.1, 3)
$(r_q^{b_2}(s), n^{b_2})$	(0.85, 10)	(0.51, 4)	(0.04, 5)	(0.22, 15)	(0.07, 12)
$(r_q^{b_3}(s), n^{b_3})$	(0.92, 5)	(0.42, 7)	(0.01, 1)	(0.31, 7)	(0.001, 4)
$(r_q^{b_4}(s), n^{b_4})$	(0.75, 2)	(0.2, 1)	(0.2, 7)	(0.72, 13)	(0.3, 5)

Table 4. Bid's offered by different sellers for good g to buyer b.

s_i	s_1	s_2	s_3	s_4	s_5
bid(q_{s_i}, p_{s_i} **)**	(47,48)	(46.2, 45)	(45.5, 52)	(48, 50)	(55,20)

Table 5. Trust of seller s_i on quality and guesses the quality of each bid from buyer b.

s_i	s_1	s_2	s_3	s_4	s_5
$\mathrm{trust}_q^b(s_i)$	0.8467	0.57152	0.1883	0.4803	0.146
$q_{s_i}^{guess}$	43.397	36.302	27.033	35.527	31.515

Table 6. Buyer b guesses the value of each bid offered by sellers.

s_i	s_1	s_2	s_3	s_4	s_5
$G^b(q_{s_i}^{guess}, p_{s_i}, s_i)$	0.2841	0.2094	0.2373	0.1701	0.293

We see that reputation on price of seller s_1 was updated with smaller value than before. It is because of this fact that maximum price expected of buyer b is smaller than price of the good it has purchased. But high quality of good g_1 delivered by s_1 ratio to what buyer b expected, increases the value of good g_1 offered by seller s_1 .

ii. Second time for good g_2: Because $\widehat{q_2} < q_{s_1}$(44<47), buyer b uses Equations 28 and 29 to update reputation on quality of seller

s_1. Also, as the earlier step, buyer b uses Equations 32 and 33 to update reputation on price because $p_b < p_{s_1} (45 < 48)$:

$$v_q = \left(1 + (1 - 0.65)\right) * \frac{44 - 47}{50} = -0.081$$

$$r_q^b(s_1) = 0.8198 + (-0.081) * (1 - 0.8198)) = 0.8052$$

$$v_p = (1 + 0.35) * \frac{45 - 48}{60} = -0.0675$$

$$r_p^b(s_1) = 0.4662 + (-0.0675) * (1 - 0.4662)) = 0.4301$$

Selling situation

Consider how a seller in the afore-said marketplace, behaves according to the proposed seller algorithm. In this example, we investigate behavior of seller s_1 in the marketplace. Assume these assumptions: we define the maximum percent of profit $k = 0.3$. Therefore, according to Equation 2, if a good costs 40 for seller s_1, then the maximum price (p_{max}) that seller s_1 can dedicate is equal to 52. We also define the real quality of good g is q_{real} =45 and reduction percent of price is *rp*=0.015.
Sellers increase cost and quality of goods in Equation 10 with the *inc* rate of 0.04.

We assume that conscientiousness score of seller s_1 ($cons_{s_1}$) and stingy score of seller s_1 ($stingy_{s_1}$) are equal to 0.9111 and 0.8, respectively. Reputation of buyer b by seller s_1 is 0.8333. We know buyer b has requested 2 goods of g, so N is equal to 2. According to Equation 3, seller s_1 adjusts his bid on quality as follows:

$$q_s = 45 + \frac{45 * (1 - 0.9111)}{2} = 47$$

Also, seller $s_1$adjusts his bid on price based on Equations 4, 5 and 6:

$$p = 40 + (52 - 40) * 0.8 = 49.6$$

$$discount = (49.6 - 40) * 0.8333 * (1 - 0.8) = 1.6$$

$$p_s = p - discount = 49.6 - 1.6 = 48$$

After that, buyer b selects s_1 as winner of auction, it sends its announcement to all sellers which they had sent bid to buyer b. Behaviors of sellers s_1 and s_3 after receiving this announcement are as follows:

Seller s_1 because he succeeds to sell some goods to buyer b, updates the reputation of buyer b based on equations 7 and 8:

$$\mu_{profit} = \frac{49.6 - 40}{52 - 40} = 0.8$$

$$r^s(b) = 0.8333 + 0.8 * (1 - 0.8333) = 0.9666$$

$$r^s(b) = 0.9666 + 0.8 * (1 - 0.9666) = 0.9933$$

We see that reputation of buyer b is updated twice because buyer b had bought 2 goods from seller s_1.

Seller s_3 should alter its bid to increase the chance to be selected by buyer b in the next auction. We assume $stingy_{s_3}, r^{s^3}(b), q_{real}$ *and* $c^{s_3}(g, q, b)$ are equal to 0.1, 0.7, 46 and 45, respectively. Seller s_3 decreases the price of good g by Equation 9:

$$p_{new} = 52 - (0.015 * 52) - \left(\frac{1 - 0.1}{10} * 0.7 * 52\right) = 47.944$$

As we said in seller algorithm, the price offered by a seller cannot be smaller than cost of production of the good. Now ($p_{new} = 47.944 > c^{s_3}(g, q, b) = 45$), therefore seller s_3 can propose the new price to buyer b in next bid on good g.

EXPERIMENTAL RESULTS

We have implemented this model with aglet (Aglet Research Group of NCKU, 2004; IBM Research, 2002) which is java based environment for building mobile and stationary agents. Our results show that stingy sellers obtain lower benefit rather than non-stingy sellers. Non-stingy seller agents consider more discount for buyer agents, therefore, they will be selected more time by buyer agents. In other word, the buyers dedicate higher value to their bids when they use estimate function to evaluate the value of each bid. Also, non- conscientious sellers sell their goods better than the other sellers for first time, But after some transactions, their reputation tear down and buyers focus their trading on conscientious sellers. Results confirm that, finally, conscientious sellers obtain more satisfaction in comparison to non- conscientious sellers. Generally, non-stingy and conscientious sellers gain maximum benefit, and stingy and non-conscientious sellers obtain lowest benefit in the market. In addition, openness and non-stingy buyers purchase more expensive and high quality goods in the market relative to stingy and non openness buyers which focus their trading on cheap and low quality goods. Moreover, buyer with high score of agreeableness will less cheat, because these buyers share their knowledge in cooperation with each other so they will know honest sellers quickly.

We have tested our proposed model, both for buyer and seller agents, in extensive experimentation. The seller agent's satisfaction and buyer agent's satisfaction are presented further.

Seller satisfaction

We have tested this model by 25 seller agents and 40 buyers, in which, each buyer does 3000 transactions in the market. Seller agents are categorized in four groups and buyer agents in 2 groups. Seller agents are divided into four groups as follows:

Group A consists of five seller agents. These are non-conscientious and stingy sellers.

Table 7. Total and Average number of sales by six groups of sellers.

Group	A	B	C	D	E	F
Total number of sales	70	650	100	1536	271	373
Average number of sales	11.66	108.33	16.66	256	45.16	62.16

Group B consists of five seller agents. These are conscientious and stingy sellers.
Group C consists of five seller agents. These are non-conscientious and non-stingy sellers.
Group D consists of five seller agents. These are conscientious and non-stingy sellers.
Group E consists of five seller agents that do not cheat buyers and use fixed bid for any buyer. They offer and deliver goods as same.
Group F consists of five seller agents. Which alter quality and price of their goods but do not model the reputation of buyers. Moreover, they do not consider discount for buyers. They start their bids and then alter their offers based on buyers' requirements.

We have assumed that all buyer agents model the reputation of sellers. In addition, there are other parameters considered for sellers:

i. Quality is chosen equal to cost to support the common assumption that it costs more to produce high quality goods. That is, a good in quality of 38 costs just 38.
ii. We define the maximum percent of profit κ = 0.2. Therefore, according to Equation 1, if a good costs 38, then the maximum price that seller s can dedicate is equal to 45.6.
iii. We assume that reduction percent of price (*rp*) in Equation 4 is equal to 0.015.
iv. Sellers increase cost and quality of goods in Equation 5 with the *inc* rate of 0.02.
v. A seller can produce goods at the maximum quality of 50.

All buyers use the buyer agents algorithm proposed in this paper and the parameters that are applied are as follows:

1. For all buyers, we suppose $\mathrm{stingy_b} = 0.35$, $\mathrm{open_b} = 0.65$ and $\mathrm{agreeable_b} = 0.5$.
2. For all buyers, reputable thresholds for quality and price are equal to 0.4, while their corresponding disreputable thresholds are -0.8 and -0.5, respectively.
3. Expected values for buyer b on quality and price are 40 and 43, respectively.
4. We define $\mu_{\min\_q}$ and $\mu_{\min\_p}$ are equals to 0.05.
5. All buyers request one good in each auction (N=1).

The results of this experiment confirm that sellers who exploit the proposed algorithms (that is, group D), achieve better satisfaction than the other sellers. In addition, buyers learn to focus their business on sellers who have reached enough reputation and prevent interaction with disreputable ones. Average and total number of sales made by each of these five groups of sellers is shown in Table 7.

Sellers of groups A and C are dishonest sellers that lie on quality because they are non-conscientious. In real markets, it is expected that when buyers purchase from a seller who tries to cheat them, they will not deal with him for their future purchases. Table 7 confirms this matter so that each buyer purchases from dishonest sellers no more than once. There are 40 buyers in the market and some of them were cheated by a dishonest seller once. Therefore each dishonest seller can cheat some buyer one time because all buyers use each other's experiences and his reputation of seller. Buyers model the reputation of dishonest seller and consider the reputation for the seller lower than disreputable threshold, θ^b, as described in Equation 17. Actually, buyers learn to stay away from disreputable sellers. Sellers of group E, offer goods in fixed quality and price. Although they may sell some of their goods in their first deals, but because of the existence of sellers of the other groups who alter their bids to offer goods in high quality, buyers will no longer purchase from sellers of this group, since they cannot visit the buyers' requirements. Sellers of group F alter their bids based on buyer requirements and they achieve further sales in comparison to sellers of groups A, C and E. Seller agents of group B made more sales rather than groups A, C, E and F. Although, these seller agents were stingy but they did not cheat the buyers and they offered the real quality of the goods.

The maximum number of sales made by group D was conscientious and non-stingy. In real markets, sellers pay tribute to buyers in order to attract and keep them as their own customers for long time. Discount is one of the important factors that sellers can promote for their own reputable buyers. Sellers of group D applied this marketing strategy to increase the number of their customers. The results shown in Table 7 confirm this hypothesis. Buyers gradually learn to purchase their required goods from sellers who offer goods in high quality while dedicating discounts.

Buyer satisfaction

In the test for validation of buyer algorithm, there are 25

Table 8. Number of purchases made by groups of buyers from sellers group.

Group of buyer/seller	A	B	C	D	E	F
Average purchases of Group I	40	4.4	32.4	2.8	2.4	2
Average purchases of Group II	35	6	50	5	2	2
Average purchases of Group III	33.4	6.2	46	6	3.6	4.8
Average purchases of Group IV	20	14	20	34.6	4.4	7
Average purchases of Group V	3	20	4	54	7.6	11.4

sellers and buyer agents each in our simulated marketplace assuming that buyers arrange a total of 2000 auctions. Seller agents are divided into six groups as described earlier. In this test, we have simulated buyer agents into five groups:

Group I consists of 5 buyer agents. These agents do not model reputation of sellers.
Group II consists of 5 buyer agents. These agents are stingy, non-openness and non-agreeable.
Group III consists of 5 buyer agents. These agents are stingy, non-openness and agreeable.
Group IV consists of 5 buyer agents. These agents are non-stingy, openness and non-agreeable.
Group V consists of 5 buyer agents. These agents are non-stingy, openness and agreeable.

The other parameters for buyers and sellers are similar to the parameters considered earlier in the work. The results of this experiment show that buyers who apply the proposed algorithm (that is, group V) achieve more satisfaction than the other buyers. Table 8 shows that each group of buyers has focused on which group of sellers for doing their trade.

We know that sellers of group E make best offers for buyers and are more honest in comparison with the other group of sellers. So we expect that buyers focus their trades on sellers of group D and then B, in order to obtain more satisfaction. Table 8 shows that buyers of group I make 40% of their purchases from sellers of group A, which are dishonest on quality and stingy and 32.4% from sellers of group B that are dishonest on quality too. Also, group I make just 4.4, 2.8, 2.4 and 2% of their purchases from groups B, D, E and F, respectively. Other sellers of groups D and B alter their bids but in comparison with group A's bid obtain less value because sellers of group A bid to buyer with very high quality and cheat buyers. So if buyer does not model the reputation of seller, it considers very high value for sellers' bid and selects them as winner in auctions much more than once. Table 8 shows that group II make 50% of their purchases from sellers of group C, because they are stingy and non-openness so they just have focused on low price of goods and were cheated by sellers of group C who lie on quality of their goods. Behavior of group III is similar to group II but there is a difference that group III are agreeableness and have used each other experiences on quality to buy goods from sellers so these group were less cheated than group II on quality by sellers of group C and A. Buyers in group IV, just as buyers in group V, have focused their trades on sellers in group D but less than group V, because they are not agreeable, therefore each dishonest seller on quality (groups A and C) has cheated them one time. Buyers in group V model the reputation of sellers on quality and have good personality and avoid interacting with disreputable sellers. This group makes 3% of their purchases with sellers of group A and 4% with group C. It means that group V evaluates the reputation of sellers and avoids interacting with disreputable less than ones because they are agreeable. Buyers in group V that apply the proposed algorithm for buyers presented in this paper have obtained more satisfaction in comparison with buyers in other groups. Buyers in group V learn to focus their trades on sellers who alter their bids and increase the quality of their goods (group B and D) and in long time learn to focus on sellers who in addition to altering bids and increasing the quality of goods, consider discount for buyers (Group D). Sellers of Group D, as described before, model the reputation of buyers and then dedicate discount for them based on their reputation. So it is expectable that buyers make more trades with sellers of group E.

Conclusion

In this paper, we proposed a market place based on reputation, personality and reinforcement learning algorithms for buying and selling agents. We consider two personality traits for seller agents: stingy and conscientiousness. Stingy seller agents are the sellers who like money so much, and try to maximize their benefits. Therefore, these seller agents consider a little discount for buyers. Also, seller agents with personality trait conscientiousness are responsible, dutiful and orderly. These sellers try to be trustful in the market. Their bids are compatible with the characteristics of their real goods. We showed that sellers who exploit the proposed algorithms with good personality (non-stingy, conscientiousness) obtain better satisfaction compared to the others. In addition, we use three personality traits for buyer agents: stinginess, openness and agreeableness.

Our results show that sellers with low score of stingy earn more benefits in comparison with high stingy sellers. Also, conscientious seller agents gain more reputation relative to conscienceless seller agents. On the other hand, buyer agents with high score of openness and low score of stingy purchase more new goods and more expensive goods relative to buyers with low score of openness and high score of stingy. Moreover, buyer with high score of agreeableness will less cheat, because these buyers share their knowledge in cooperation with each other, so they will know honest sellers quickly who present best promotion and accordingly will stay away altogether from dishonest sellers. Therefore, the profits of those buyers will quickly increase. We have investigated this fact that marketing and consumer relationship management are two important factors in business, so that sellers who obey this fact construct better reputation for themselves among buyers and get greater profit in comparison to the others. This model is very flexible to develop marketing purposes and modeling a real market completely. However, proposed model and algorithms can be improved so that both sellers and buyers who exploit the improved model can obtain best results as fast as possible.

We try to apply more personality traits of Big Five in electronic marketplace. Also, according to the nature of personality which is fuzzy, we model the personality in fuzzy and specify the rules related to personality and buyer and seller behavior. The other important factor is culture which profoundly affects the buyer behavior in the market. Our future work concentrates on using culture in agent-based marketplaces.

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